New Plants as Natural Experiments in Economic Adjustment: Adjustment costs, learning-by-doing and lumpy investment

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Abstract: A large sample of new plants is studied to reveal detailed adjustment behavior for capital, labor and productivity. Capital and labor both adjust rapidly. Overall, capital adjustment is lumpy while labor follows a learning-by-doing model rather than a convex adjustment cost model. Plants are quite heterogeneous, however: convex adjustment costs appear important at small plants, but large plants exhibit lumpy investment and substantial investment in learning-by-doing. A positive association between plant productivity growth and wages (and also the change in wages) corroborates the importance of learning-by-doing. Also, learning-by-doing appears to influence the behavior of large plants subsequent to startup.

Keywords: Adjustment costs, learning-by-doing, capital investment, productivity

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I. Introduction

Empirical economists have long recognized that economic variables often adjust only slowly to “shocks” in demand or technology. A variety of theoretical explanations have been advanced to explain slow adjustment. Input factors adjust slowly because of convex adjustment costs, or because of time-to-build, or because of irreversibility of investment in the face of uncertainty. Productivity adjusts slowly because of learning-by-doing.

A complete picture of adjustment might incorporate all of these models and so it would be helpful to understand the relative empirical significance of each explanation. Unfortunately, this is often econometrically difficult. It is difficult to identify a general model without making strong assumptions about the nature of adjustment, especially in a world with heterogeneous capital and labor and with heterogeneous plants (hence possibly different adjustment costs, etc.).

However, important clues about adjustment are revealed at the startup of new plants. Under the assumption that each new plant is created in response to a large positive shock (and that the mean of subsequent shocks is much smaller), the observed mean behavior of new plants directly reveals the pattern of adjustment to this shock. That is, new plants make a natural economic experiment in adjustment.

This paper uses a large, representative sample of new manufacturing plants to examine the adjustments of capital, labor and productivity. Using five years of data for each plant, it is possible to measure the extent of “lumpy” adjustment relative to the extent of smooth adjustment (flexible accelerator) for capital and different types of labor. It is also possible to distinguish different patterns of adjustment corresponding to different theoretical models and to observe changes in these patterns across different types of plants.

This investigation finds that the adjustment of capital is lumpy rather than smooth and that the adjustment of labor is best explained by a learning-by-doing model, rather than by models of convex adjustment costs, time-to-build or neutral technical change. The convex adjustment cost model does seem to apply, however, to small plants.

About 80% of capital is in place the first year of operations, 90% for large plants, suggesting a lumpy and rather rapid adjustment for capital. An econometric model that nests both an initial lumpy investment and smooth “flexible accelerator” adjustment finds that 75% of investment is lumpy. And even the smoothly adjusting portion adjusts rather rapidly, with a mean lag (excluding the initial lump) of about a year.

Labor adapts in a manner not statistically inconsistent with the partial adjustment model. However, labor’s adjustment is inconsistent with a simple model of convex adjustment costs.

Convex adjustment costs imply that capital intensity (capital to labor ratio) should decrease over the course of the ramp-up as labor rises to its target level. Correspondingly, labor productivity should fall, although multi-factor productivity should remain unchanged. In fact, capital intensity does not fall (it rises for large plants), and both labor and multi-factor productivity exhibit strong growth consistent with a learning-by-doing model. Indeed, large plants actually *decrease* their workforce over the course of ramping up, contradicting convex adjustment cost models.

However, these adjustment patterns are not uniform across all plants. Adjustment behavior is not homogenous, contrary to a common assumption. Small plants, especially plants with 10 or fewer employees, *do* behave in line with the convex adjustment cost model for both capital and labor. It appears that there may be substantial economies of scale in adjustment costs. Nevertheless, the overall pattern of adjustment for plants of all sizes does not conform to the convex adjustment cost model.

On the other hand, learning-by-doing appears to play a particularly strong role among large plants. Calculating the implicit adjustment cost as the foregone output (the additional output a plant could have produced without the lower level of productivity during the initial years), large plants as a group spend about $37,000 per employee in 1987 dollars. This can be viewed as an intangible investment in learning-by-doing. This quantity is sizeable either by comparison to other estimates of adjustment costs or by comparison to physical investment.

Moreover, the importance of learning-by-doing is corroborated by wage patterns. The model of learning-by-doing assumes that productivity rises as the result of improved labor quality. Labor quality could improve as workers learn new skills through experience. Alternately, it could improve as managers gain information about workers over time and are able to select out better quality workers. In either case, wage levels and the change in wages over the ramp-up should both be related to productivity growth. Regressions on plant level wages and salaries for both production and non-production workers, and the changes in these variables all find a positive and significant relationship with plant productivity growth. Finally, some evidence is presented that learning-by-doing continues to influence labor adjustments long after startup.

This paper is organized as follows. Section II reviews the overall summary statistics for the sample of new plants and explores the time structure of adjustments. Section III explores in greater detail four candidate theories for explaining the labor adjustment. Section IV provides additional evidence on the significance of learning-by-doing and Section V concludes.

II. The overall patterns of adjustment

Summary statistics

The sample of new plants was drawn from the Longitudinal Research Database (LRD) of manufacturing plants developed by the Center for Economic Studies of the U.S. Bureau of the Census [McGuckin and Pascoe, 1988] for years 1972 – 1992. This database is derived from the Census of Manufactures, which surveys all manufacturing plants every five years, and the Annual Survey of Manufactures, conducted on a sub-sample during interim years. The database is constructed to be representative of the entire manufacturing sector.

Since the analysis requires five consecutive years of data, the selection of plants for this sample tended to favor somewhat larger plants and plants owned by multi-plant firms. To correct for this, a set of sample weights was developed so that the weighted sample matched the characteristics of all new plants in the Census of Manufactures. Details of this procedure and of data construction are presented in the Appendix. Unless mentioned otherwise, sample weights are used throughout. Analysis using unweighted data was not found to substantively alter results. After applying screens for reporting error, the sample contained 5,625 plants.

Table 1 displays summary statistics for the first five years of these plants and Figure 1 displays mean levels of several variables compared to their mean levels in the fifth year. Several features stand out. All the variables (except wages and salaries, which stay more or less constant) do tend to converge to their fifth year levels and the absolute rate of convergence slows. Clearly, *most* of the adjustment takes place the first year for all variables.

Also, note that capital and labor tend to adjust at about the same rate; non-production workers, materials, inventories and output adjust at somewhat more rapid rates. The faster rate of output growth suggests productivity improvement.

The time structure of adjustment: smooth or lumpy?

The general impression of these statistics is hardly a picture of slow partial adjustment. But could the adjustments be rapid but nevertheless smooth? Or are they lumpy, that is, are they distinctively *more* rapid the first year? A simple econometric model can help distinguish between these two cases.

Two different sorts of theory have been used to describe adjustment behavior. On the one hand, changes in input levels have been assumed to generate convex costs of adjustment. Larger changes incur proportionately larger costs, and so firms are induced to adjust inputs slowly over time [Lucas, 1967; Eisner and Strotz, 1963; Treadway, 1969]. Often adjustment costs are assumed to be quadratic and this generates the standard partial adjustment model used widely in macroeconomic empirical work. On the other hand, if changes in input levels represent an irreversible investment or if adjustment costs are non-convex, then firms may wait until the target level of that input exceeds a threshold and then invest all at once. The most comprehensive models of this sort of "lumpy" investment have used options theory [Dixit and Pindyck, 1994].[1]

To analyze the adjustment patterns of new plants it is helpful to have a single model that nests both smooth and lumpy adjustment. To start with, consider the standard partial adjustment or "flexible accelerator" model of smooth adjustment:

(1a) $$\Delta K_t = \lambda \cdot \left(K_t^* - K_{t-1}\right), \qquad \Delta K_t \equiv K_t - K_{t-1} \text{ or}$$

(1b) $$K_t = (1-\lambda) \cdot K_{t-1} + \lambda \cdot K_t^*$$

where K is the input factor, K* is the "target" or long-run level of the input factor, t designates time period (t = 0, 1,…) and λ is a constant such that $0 < \lambda \leq 1$. It is helpful to think of K as capital, although the model applies to other inputs as well. Such a model could result from quadratic adjustment costs in K, although it also serves more generally as an approximation to other patterns of smooth adjustment.[2]

In fact, a pattern of smooth adjustment after the first period, as observed in Figure 1, might not result from convex adjustment costs at all. Such investment could actually be "lumpy"—as in Dixit and Pindyck [1994]. If investment is irreversible, the firm may wait until K* exceeds some threshold and then it will commit to the full investment of this amount. However, time-to-build considerations might cause some portion of this investment to be delayed so that it approximately follows (1).

Obviously, a fully general model that incorporates all such possibilities cannot be identified. However, one could assume that lumpy investment occurs *only* during the initial period. This assumption implies that any estimates of the portion of lumpy investment may be understated and hence considered lower bound estimates. The firm would make the entire desired investment at

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[1] In addition to these models of adjustment, the measurement of adjustment must also be concerned with possible time-to-build delays [Kydland and Prescott].

[2] It is, of course, possible that λ could vary from year to year in a partial adjustment model. But the approach here is to assume a constant proportional adjustment, estimate this using data from the second through fifth years, and then determine whether the rate of adjustment is significantly different during the first year.

once, so that the pattern for a startup experiencing a large initial shock would be $K_0 = K_0^*$ and $K_t = K_0$, $t = 1,2,\ldots$ until another sufficiently large shock induced additional investment.[3]

It is possible to nest this simple model of lumpy investment with the standard model of smooth adjustment, (1). Assume that the quantity K is actually composed of heterogeneous goods, some adjusting smoothly, others adjusting in a lumpy fashion. Assume that l percent of the target investment is lumpy ($0 \le l \le 1$), so that total lumpy investment is $l \cdot K_0^*$, the remainder being smoothly adjusting capital. Then a simple nested model using form (1b) is

$$\begin{aligned} K_0 &= (1-\lambda)\cdot l \cdot K_0^* + \lambda \cdot K_0^* = (l - \lambda \cdot l + \lambda)\cdot K_0^* \\ K_t &= (1-\lambda)\cdot K_{t-1} + \lambda \cdot K_t^*, \qquad t = 1,2,\ldots \end{aligned} \tag{2}$$

Note that when l = 0, this reverts to (1), and when l = 1 this reverts to the pure lumpy model.

The terms $\lambda \cdot K_t^*$ represent unobserved plant fixed effects, so it is desirable to remove them. Taking first differences, solving for K_0^*, and adding a stochastic term yields

$$\begin{aligned} \Delta K_1 &= (1-\lambda)\cdot\left(K_0 - l\cdot K_0^*\right) + \varepsilon_1 = (1-\lambda)\cdot K_0 \cdot\left(1 - \frac{l}{l - \lambda l + \lambda}\right) + \varepsilon_1 \\ \Delta K_t &= (1-\lambda)\cdot \Delta K_{t-1} + \varepsilon_t, \qquad t = 2,3,\ldots \\ \varepsilon_t &\equiv \lambda\cdot\left(K_t^* - K_{t-1}^*\right) + \mu_t \end{aligned} \tag{3}$$

where μ is a stationary zero-mean disturbance representing other sources of variation. The term involving l represents the extent to which the rate of proportional adjustment is more rapid during the first period than in later periods.

Now the target level, K_t^*, evolves according to a stochastic process. This can be analyzed as a series of "shocks:" an initial shock, K_0^*, and a series of secondary shocks, $K_t^* - K_{t-1}^*$. However, consistent with the partial adjustment theory, if one assumes that the firm uses all available information in forming the long-run targets K_t^*, then the secondary shocks should have zero mean and should be uncorrelated with K_{t-1}^* and any previous target. Any correlation or non-zero mean implies that common information was not used in forming these targets. Thus

[3] The model ignores additional episodes of (positive) lumpy investment. To the extent that they occur means that the estimates of smooth adjustment are somewhat overstated and the estimates of lumpy adjustment are understated. Note also that the model ignores disinvestment. Some plants did experience declines in their capital stocks, much of it through depreciation (see Appendix) but some also from actual retirements. The heaviest retirement activity occurred during the first year or so, so this would seem unlikely to be actual evidence of substantial disinvestment. Instead this is more likely the retirement of incorrect or excess capacity due to initial mistakes.

(4) $$E[\varepsilon_t] = 0, \quad \mathrm{cov}(\varepsilon_t, K^*_{t-j}) = 0, \quad j = 1,\ldots,T .$$

In other words, K^*_t follows a random walk.

Now applying (2) or (3) recursively, K_{t-1} and ΔK_{t-1} can be written as functions of the parameters and of $K^*_{t-2},\ldots,K^*_0$. Therefore it must be true that

(5) $$E[\varepsilon_t \cdot K_{t-1}] = E[\varepsilon_t \cdot \Delta K_{t-1}] = 0$$

This means that the system of equations (3) can be jointly estimated or, alternately, the moment conditions (5) can be estimated using the Generalized Method of Moments (GMM).

Estimation of the model

The analysis of this system of equations began with a specification test. Examining capital variables first, the unrestricted model was tested against the restriction that $l = 0$. This restriction was rejected at the 1% level for capital and also for capital plus rental capital.

Given this, the model was estimated for the capital variables (see Table 2). The estimate of l was roughly 75%—three quarters of investment appears to occur in an initial lump. The adjustment of capital is substantially more rapid (proportionately) the first year than in later years. This result supports the lumpy investment model, is inconsistent with a simple quadratic adjustment cost model, and may be problematic for more general models of partial adjustment.

Moreover, the rapidity of the smooth portion of the adjustment (after the initial lump) may also be a problem for partial adjustment models. The estimates for λ are relatively high compared to other studies, implying that the partial adjustment model cannot explain long delays in adjustment.

This can be seen as follows. A common yardstick for comparing rates of adjustment is the mean lag following a single shock:

$$L = \sum_{t=0}^{\infty} t \cdot \Delta K_t \Big/ \sum_{t=0}^{\infty} \Delta K_t .$$

For startup plants, a portion of the total lag occurs prior to production. That is, after experiencing a positive shock firms may wait before committing to new capital (consistent with options theory); they may then experience delivery delays and time-to-build delays before production can begin. The duration of these delays is not evident in our data. It is possible, however, to estimate the lags that occur *after* production begins by using the model above. Re-arranging (2) and (3) and allowing only an initial shock yields

$$\begin{aligned} \Delta K_0 &= K_0 = \lambda \cdot (1-l) \cdot K_0^* + l \cdot K_0^* \\ \Delta K_t &= \lambda \cdot (1-l) \cdot (1-\lambda)^t \cdot K_0^*, \qquad t = 1, 2, \ldots \end{aligned} \tag{6}$$

so that

$$L = \frac{\lambda \cdot (1-l) \cdot K_0^* \cdot \sum_{t=1}^{\infty} t \cdot (1-\lambda)^t}{l \cdot K_0^* + \lambda \cdot (1-l) \cdot K_0^* \cdot \sum_{t=0}^{\infty} (1-\lambda)^t} = \frac{(1-l)(1-\lambda)}{\lambda}. \tag{7}$$

Values of L are shown in Table 2. Bearing in mind that these values exclude pre-production delays, they are far shorter than typical estimates based on continuous time series for established plants. Such estimates tend to run around two to three years and sometimes much longer ([Almon, 1968, Coen and Hickman, 1970, Jorgenson and Siebert, 1968, Jorgenson and Stephenson, 1967, Mohnen, et. alia, 1986, Morrison and Berndt, 1981]). The implication is that the longer delays estimated in these studies result from decision delays, delivery lags and time-to-build and *not* from a slow partial adjustment process.

It is possible that the GMM estimates have overstated λ and hence have understated the mean lags. Because the GMM estimates are based on first-differencing, any measurement error will tend to attenuate the estimates (in this case, biasing λ toward 1) [Griliches and Hausman, 1986]. To counter this effect, it is possible to estimate λ using OLS in levels with fixed effects; it is not possible to estimate l with this method, however. Taking (2) and *excluding* the first year, the ith plant will follow

$$\begin{aligned} K_{it} &= (1-\lambda) \cdot K_{i,t-1} + \alpha_i + \upsilon_{it}, \qquad t = 1, 2, \ldots \\ \alpha_i &\equiv \lambda \cdot K_{i0}^*, \qquad \upsilon_{it} = \lambda \cdot (K_{it}^* - K_{i0}^*) + \mu_{it} \end{aligned}$$

where υ is a disturbance term (zero mean, uncorrelated), μ represents other sources of variation, and α is the plant fixed effect. This can be estimated using a standard OLS fixed effects model and results are shown in Table 2. As can be seen, the mean lag *excluding* the effect of the first year is about a year, still rather rapid. Using this estimate for λ and a value of l of .739 yields a total mean lag, including the initial lump, of .27 years, just over three months.

Finally, it is also possible that some production may have occurred prior to the first year recorded in the data.[4] The estimated size of the lump, l, may then include some partial adjustment occurring prior to the first recorded year. However, even allowing for as much as six months of prior production, the majority of investment would still occur in an initial lump.[5]

To summarize, the evidence on the timing of investment at new plants suggests that only a minority of investment fits a partial adjustment model, most investment being lumpy. Moreover, the pace of adjustment is relatively quick for investment that does occur after the initial year.

The picture is quite different, however, for labor. For each of the three measures of labor, restricting the equations to the partial adjustment model is not rejected.[6] The converse is not necessarily true, however: “lumpy” adjustment cannot be ruled out. In particular, when adjustment is quite rapid, as in the case of the labor variables, it is difficult to discern the difference between smooth and lumpy adjustment both conceptually and econometrically.

OLS estimates of mean lags for production workers and production hours (.57 and .49 years respectively) correspond reasonably well with estimates based on quarterly data [Hamermesh, 1993, p. 256].[7] The mean lag for non-production workers is substantially longer.

In summary, the time structure of adjustments among new plants indicates that all adjustments are rapid. In addition, capital appears to adjust in a rather lumpy manner with a disproportionate share of investment occurring the first year.

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[4] To qualify as a startup, the plant had to indicate on a questionnaire that the first year of data was also its first year of operation and no previous record for this plant could exist in the LRD. However, it is possible that some plants may have had a few months of operation in the year preceding the first year of data collected.

[5] If $\hat{l}$ is the estimated value based on the assumption that the first period is of one year duration and l is the true value based on an actual duration for the first period of $t > 1$, then using the second equation of (6), $(1-\lambda)(1-\hat{l})=(1-\lambda)^t(1-l)$. Solving this for $t = 1.5$, yields an estimate for l of .54 for capital. Using the lower values of λ implied by the OLS analysis yields even higher estimates.

[6] The unrestricted model estimates did not converge some of the labor variables so a slightly more general model was tested. The first equation in (3) was re-written $\Delta K_1 = (1-\lambda_1) \cdot K_0$. The restriction then imposed was that $\lambda_1 = \lambda$. This is the test reported in the table.

[7] The studies based on quarterly data surveyed by Hamermesh have an average median lag of .35 years. Estimates based on data of longer periodicity are larger but these may suffer from aggregation bias.

III. The nature of the adjustment of labor

Models and evidence on the adjustment of labor

It is possible to explore the nature of the labor adjustment further by examining changes in capital intensity (capital to labor ratio), labor productivity and multi-factor productivity. Different theories of adjustment for labor imply different patterns of change in these three variables. Consider, for instance, convex adjustment costs for labor given an initial lumpy investment in capital. In this model, the labor force only reaches its desired target level after some time, so one would expect capital intensity to decrease over the course of the plant ramp-up (assuming the capital stock remained relatively unchanged). Consequently, labor productivity would exhibit a corresponding decrease although multi-factor productivity would remain unchanged.

If, however, the adjustment of labor is driven by other causes, then the capital intensity and productivity measures may grow according to different patterns over the course of the first several years. For example, learning-by-doing models typically imply that both labor productivity and multi-factor productivity should increase, contradicting the simple convex adjustment cost model.

This intuition can be elaborated a bit more formally. As above, assume that the startup of a new plant is in response to a large positive shock and that on average plants will approach an equilibrium level over the course of the ramp-up. This means that the average behavior of a large number of plants can be studied using models of adjustment to equilibrium. Even though these plants will experience secondary shocks, these shocks will have different signs and should have a mean near zero, at least by comparison to the initial shock. Thus if, say, the equilibrium adjustment model indicates a declining capital intensity, then one would expect capital intensity to decline on average for a large sample of new plants. Making this assumption that startup behavior represents an adjustment toward equilibrium, different models can be developed for convex adjustment costs, time-to-build, Hicks neutral technical change, and learning-by-doing (labor-specific productivity change).

Consider a two-factor model of two periods followed by an infinitely long equilibrium period (the "long run"). The two inputs are labor and capital, L_t and K_t , $t=1,2$. The second period levels of inputs are the equilibrium levels. Prices are static, output price is numeraire, and labor costs *w*. Let the production function be Cobb Douglas so that

$$Q_t\left(K_t, L_t\right) = A_t \cdot K_t^{\alpha} \cdot L_t^{1-\alpha}$$

where A is a productivity measure. This is a very simple model that could be generalized to allow non-static price expectations, secondary shocks, etc., at some cost to the simplicity of exposition. The results derived here, however, also hold for a range of more complicated models. Consider first a model with convex adjust costs for labor:

Convex labor adjustment costs. Assume an adjustment cost function $c(L_t - L_{t-1})$. That is, a new plant would incur adjustment costs of $c(L_1)$ during the first period, costs of $c(L_2 - L_1)$ during the second period and no adjustment costs thereafter.[8] $c(\cdot)$ is assumed to be convex, that is, $c' > 0,\ c'' > 0$. Also, in a pure model of convex adjustment costs, there is no technical change, so $A_1 = A_2$.

Given a discount rate r such that r << 1, the present value of cash flow is (ignoring discounting for the second period), is then

$$
\begin{aligned}
V = {} & Q(K_1, L_1) - w \cdot L_1 - c(L_1) \\
& + Q(K_2, L_2) - w \cdot L_2 - c(L_2 - L_1) \\
& + \frac{1}{r} \cdot \left(Q(K_2, L_2) - w \cdot L_2\right)
\end{aligned}
\tag{8}
$$

Now since r << 1, the first order condition for L_2 is approximately

$$
\frac{\partial V}{\partial L_2} \approx \frac{\partial Q(K_2, L_2)}{\partial L} - w = 0 \text{ or } \qquad w = (1-\alpha) \cdot A_2 \cdot \left(\frac{K_2}{L_2}\right)^{\alpha}.
\tag{9}
$$

This is just the long run equilibrium condition. Substituting this expression for w into the first order condition for L_1 yields

$$
\frac{\partial V}{\partial L_1} = (1-\alpha) \cdot A_1 \cdot \left(\frac{K_1}{L_1}\right)^{\alpha} - (1-\alpha) \cdot A_2 \cdot \left(\frac{K_2}{L_2}\right)^{\alpha} - c'(L_1) + c'(L_2 - L_1) = 0.
$$

Now the convexity of c and the condition $\frac{1}{2}K_2 < K_1 \le K_2$ imply that $L_1 > L_2 - L_1$ thus $c'(L_1) > c'(L_2 - L_1)$ so[9], considering that $A_1 = A_2$,

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[8] A more complex model might consider $c(\cdot)$ to also be a function of K and/or the change in K. For simplicity, this model considers capital adjustment costs to be separable and, instead, simply assumes that the optimal capital levels are such that $\frac{1}{2}K_2 < K_1 \le K_2$, consistent with the empirical evidence on mean capital levels.

[9] If $L_1 < L_2 - L_1$ were true, then $\frac{K_1}{L_1} < \frac{K_2}{L_2}$ or $K_1 < \frac{L_1}{L_2}K_2 < \frac{1}{2}K_2$ so this violates the restriction on K that is consistent with observed behavior. In more sophisticated models this case is excluded by a transversality condition.

$$\frac{K_1}{L_1} > \frac{K_2}{L_2}$$

or, in other words, capital intensity decreases. One can readily calculate that the ratio of labor productivity between the third and first periods is

$$\frac{Q_2}{L_2} \cdot \frac{L_1}{Q_1} = \left(\frac{K_2}{L_2} \cdot \frac{L_1}{K_1} \right)^{\alpha} < 1$$

so labor productivity also declines. Finally, multi-factor productivity can be defined as

$$M_t \equiv \frac{Q_t}{K_t^{\alpha} L_t^{1-\alpha}} \qquad \text{so that } \frac{M_2}{M_1} = \frac{A_2}{A_1} = 1.$$

Thus this simple model indicates that convex labor adjustment costs imply declining capital intensity and declining labor productivity and unchanged multi-factor productivity. Several other simple "pure" models can be considered as well:

Time-to-build. As discussed above, capital time-to-build may impose unobserved delays prior to first production. However, it is also possible that time-to-build may affect labor adjustment once production has begun. If some portion of K_1 is still under construction, then the *effective* capital stock during the first period will be less than K_1. Let the effective stock of capital during period 1 be $u \cdot K_1$, $u < 1$. Then $Q_1 = A_1 \cdot (uK_1)^{\alpha} L_1^{1-\alpha}$. Then assuming no adjustment costs and solving the first order conditions as above yields

$$\frac{K_2}{L_2} \cdot \frac{L_1}{K_1} = u < 1, \qquad \frac{Q_2}{L_2} \cdot \frac{L_1}{Q_1} = \left(\frac{K_2}{L_2} \cdot \frac{L_1}{uK_1} \right)^{\alpha} = 1, \qquad \frac{M_2}{M_1} = \left(\frac{K_2}{L_2} \cdot \frac{L_1}{K_1} \right)^{\alpha} > 1$$

or, capital intensity declines, labor productivity is unchanged and multi-factor productivity increases.

Hicks Neutral Productivity Change. Now consider a model where there are no adjustment costs, no time-to-build after the onset of production, but where productivity increases neutrally over the course of plant ramp-up. That is, $A_2 > A_1$. This could be due to exogenous technical change or to economies of scale (not captured in the production function). It could also be due to "managerial" learning-by-doing where the productivity gains are not related to specific labor. In this case, the above system solves to

$$\frac{K_2}{L_2}\cdot\frac{L_1}{K_1} = \left(\frac{A_1}{A_2}\right)^{1/\alpha} < 1, \quad \frac{Q_2}{L_2}\cdot\frac{L_1}{Q_1} = \frac{A_2}{A_1}\left(\frac{K_2}{L_2}\cdot\frac{L_1}{K_1}\right)^{\alpha} = 1, \quad \frac{M_2}{M_1} = \frac{A_2}{A_1} > 1$$

so that in this case also capital intensity declines, labor productivity is unchanged and multi-factor productivity increases.

Learning-by-doing. In some common models of learning-by-doing, productivity at a new plant increases as the result of improving quality of the labor force. This might be because workers learn from experience on the job (human capital model). Or it might be because employers are able to learn the true productivity of different workers and then fire less productive workers (selection model).[10] In either case, a given group of workers must be on the job for a given period before their labor quality is augmented. That is, let the *effective* first period labor force be $h\cdot L_1$, $h < 1$.

Similarly, assuming that workers become fully effective after one period *and* if $L_1 < L_2$, then the effective labor during the second period is $L_1 + h\cdot(L_2 - L_1)$ and is simply L_2 thereafter. If, on the other hand, $L_1 \geq L_2$, then the second period labor force can be assumed to consist of workers who are already fully productive, and so the effective labor force is just L_2 in the second period and thereafter.[11]

Following the calculations above and using the first order condition on L_2 yields

$$\frac{\partial V}{\partial L_1} = \left\{ \begin{matrix} w\cdot h^{1-\alpha}\left(\frac{K_1L_2}{L_1K_2}\right)^{\alpha} - w + w\cdot(1-h)\cdot\left(\frac{L_2}{L_1+h(L_2-L_1)}\right)^{\alpha} \text{ for } L_1 < L_2 \\ w\cdot h^{1-\alpha}\left(\frac{K_1L_2}{L_1K_2}\right)^{\alpha} - w \text{ for } L_1 \geq L_2 \end{matrix} \right\}.$$

Now by examining $\left.\frac{\partial V}{\partial L_1}\right|_{L_1=L_2}$ one can demonstrate that an interior solution (where $L_1 < L_2$) occurs only when $h\cdot K_2 > K_1$, otherwise, $L_1 = L_2$. When this condition for an interior solution does not

[10] Although cases of neutral technical change might also be described as “learning-by-doing” the phrase will be applied here only to models where productivity increases as the result of improved labor quality.

[11] In a more sophisticated selection model, the relative sizes of L_1 and L_2 might be determined exogenously by the nature of the selection process. In this case, the change in capital intensity would be indeterminate.

obtain, learning-by-doing acts as a non-convex adjustment cost and labor is hoarded.[12] In this latter case, since $K_1 \leq K_2$ it must be true that

$$\frac{K_1}{L_1} \leq \frac{K_2}{L_2}$$

or, in other words, capital intensity is non-decreasing (for the interior solution, capital intensity is strictly increasing). Then, comparing the third to first periods, it also follows that

$$\frac{Q_2}{L_2} \cdot \frac{L_1}{Q_1} = \left(\frac{K_2 L_1}{L_2 K_1}\right)^{\alpha} \cdot \frac{1}{h^{1-\alpha}} > 1, \qquad \frac{M_2}{M_1} = \frac{1}{h^{1-\alpha}} > 1\,.$$

That is, for the learning-by-doing model, capital intensity it non-decreasing and both labor productivity and multi-factor productivity increase.

* * * *

The characteristic behavior for each of these four models is summarized in Table 3. The table also summarizes sample evidence, reporting both aggregate changes in capital intensity and labor and multi-factor productivity and mean changes in these quantities for individual plants.

These four models represent "pure" effects. It is possible that plants may experience combinations of the various effects or that different effects may dominate different plants. Some dimensions of plant heterogeneity are explored below. Nevertheless, one or another effect may dominate.

This appears to be the case: both the aggregate and mean changes fit the learning-by-doing model. For production workers, the change in capital intensity is not significantly different from zero and labor productivity exhibits a statistically significant increase. The increase in multi-factor productivity is positive and statistically significant and it is also significantly larger than would be expected according to the time-to-build model.[13] When non-production workers are included the

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[12] In this simple model, solutions where $L_1 > L_2$ violate the assumption about K however a more sophisticated model might allow this possibility especially in the context of a selection model. In fact, below evidence is presented that some plants do shed workers.

[13] Multi-factor productivity is calculated as a Divisia index: $\Delta \ln M = \ln \frac{Q_5}{Q_1} - \sum_i \tfrac{1}{2}\left(s_{i1} + s_{i5}\right) \cdot \ln \frac{X_{i5}}{X_{i1}}$ where the X_{it} are input factors production hours, non-production workers, materials and capital and the s_{it} are output shares. The output shares for labor inputs assume a 17% supplementary cost over actual wages (this is the mean excess of total employment compensation to wages and salaries in the NIPA series for manufacturing 1972-87) and the capital share is calculated using the BLS rental rates. Capital includes imputed rental capital. Two alternate versions of multi-factor productivity were also calculated. To correct for possible changes in labor quality, one version used efficiency units (wage-weighted) for labor; the change (and standard error) for this measure was .062 (.005). Second, because adjustment shadow costs might cause output shares to deviate from output elasticities, productivity was also calculated using only 5th year shares for labor and capital. The productivity change (and standard error) for this measure was .046 (.006).

case is weakened slightly (the mean increase in labor productivity is no longer statistically significant), suggesting that learning-by-doing may be less dominant for non-production workers.

The dominance of the labor learning-by-doing model suggests that this sort of learning-by-doing plays an important role at new plants. This does not imply that other factors such as convex adjustment costs do not also play a role, just that these factors are necessarily less significant. For example, in a mixed model with both learning-by-doing and convex adjustment costs, the adjustment costs must be small enough so that they do not exert much influence on capital intensity and labor productivity. The examination of plant heterogeneity in the next section reveals more about the relative influences of these models.

Heterogeneous adjustment patterns

The analysis so far has assumed that all plants behave similarly. This is a common assumption in the literature on adjustment. This section explores adjustment behavior along two dimensions: the initial plant size (ranked by total employees the first year) and whether the plant was initially owned by a firm that owned other plants or not. Characteristics of these different sub-groups are shown in Table 5.

Since the analysis concerns dynamic behavior, it is important to verify the relative stability of these groupings. For example, if 10 person plants are just transitorily-small 200 person plants, then any analysis based on initial size might be misleading. Table 4 shows the final characteristics based on initial status. As can be seen, only rarely do 10 person plants become 200 person plants and with the exception of one category (1-10 person plants becoming 11-50 person plants) the majority of plants maintain their original classification.

Using these classifications, one can perform the same analysis on the time structure of adjustment as in Table 2 and the pattern of labor adjustment as in Table 3 for each group separately. Table 6 shows selected statistics of the unrestricted and restricted model of lumpy and smooth adjustment. Distinct differences emerge in the lumpiness of investment: small plants (50 or fewer employees) and plants owned by single-plant firms fail to reject the restriction to the smooth-adjustment-only model. Also the labor adjustments, estimated in levels without the first year, seem to be somewhat faster among the smallest group of plants (10 or fewer employees).

Finally, as indicated in the table, the time-to-build adjustment was calculated with the additional term; this is equivalent to calculating the Divisia index using the growth rate of production labor in place of the growth rate of capital.

Turning now to patterns of labor adjustment in Table 7, different size plants again display sharply different behavior. The largest plants conform to the learning-by-doing model, with strong and statistically significant gains in capital intensity and labor and multi-factor productivity. Note that the largest plants actually *decrease* their labor forces over the course of the ramp-up, consistent with a learning-by-doing model that involves selection of more productive workers. On the other hand, the smallest plants exhibit behavior that suggests both convex adjustment costs and learning-by-doing. The smallest plants have declining capital intensity and declining labor productivity, but rising multi-factor productivity. The increase in multi-factor productivity is not nearly so large, once the adjustment for time-to-build is added in, but it is still significantly positive.

The patterns related to the number of plants owned are not quite so clear. Plants owned by multi-plant firms show stronger labor productivity and multi-factor productivity growth, but they also show declining capital intensity as opposed to significantly increasing capital intensity at single plant firms. Plants in multi-plant firms do tend to be larger and so one would expect both productivity growth measures to be larger for these plants, but one might also expect capital intensity to increase. One clue is the sharp drop in multi-plant multi-factor productivity when adjusted for time-to-build. It may be that multi-plant firms acquire capital faster, as noted above, but then face larger time-to-build effects because of this.

More generally, the different patterns of adjustment behavior by plant size and single/multi-plant status suggest significant economies in adjustment costs. At very small plants with only one or two non-production workers, management tasks necessarily compete with the demands of production. The time necessary to hire labor and to install new equipment may require a relatively large and costly diversion of scarce managerial resources away from production. At larger plants with specialized personnel departments, equipment maintenance departments and ample numbers of dedicated production managers, these costs may be relatively much smaller. Therefore at larger plants, these costs may be less significant determinants of labor adjustment behavior than learning-by-doing. Also, at larger plants adjustment costs may be a relatively smaller factor than the irreversibility of capital in determining investment timing.[14]

[14] Labor does adjust faster at small plants than at large, however, this interpretation suggests that the adjustment process at the large plants is not primarily driven by convex adjustment costs and so one cannot infer anything about relative adjustment costs from the speed of adjustment. Note also that small plants do show productivity gains suggesting that although they face significant convex adjustment costs, they also experience some learning-by-doing.

Similarly, firms owning multiple plants may have centralized support for capital budgeting, acquisition and installation and for personnel functions. Again, these may reduce the significance of adjustment costs. The more rapid acquisition of capital may, however, generate a larger degree of temporarily unusable capacity resulting from time-to-build constraints.

To summarize, the common assumption of homogenous adjustment across plants is not supported. Small plants and plants in single plant firms do behave quite differently from larger plants and from those facilities in multi-plant firms. Overall, the larger plants tend to dominate the aggregate statistics. And among these, the adjustment of capital is lumpy and learning-by-doing characterizes the labor adjustment.

IV. Further exploration of learning-by-doing

The investment in learning-by-doing

Given the apparent significance of learning-by-doing, it makes sense to explore this in greater depth. To start with, it helps to have a more revealing measure of the implicit cost of adjustment associated with learning-by-doing. The change in productivity associated with learning-by-doing, $\Delta \ln M$, does not reveal the full extent of adjustment because it does not capture the duration of the adjustment. That is, a given productivity change can be achieved quickly or slowly, but in the latter case the cumulative output can be far greater. Following the literature on implicit costs of adjustment (see for example [Lucas, 1967]), the total cost can measured as the total foregone output. Assuming that the adjustment is complete by the fifth year, this can be measured as the "learning investment"

$$I \;\equiv\; \sum_{t=1}^{4} Q_t \cdot \left(e^{\Delta_{t5} \ln M} - 1 \right)$$

where $\Delta_{t5} \ln M$ is a Divisia index of the change in log productivity between year t and year 5.

This quantity can be considered an investment in two senses. First, in a market with free entry, such that $V = 0$, this foregone output represents the cost of entry, a cashflow investment that is repaid with the profit stream $Q(K_2, L_2) - w \cdot L_2$.

Second, to the extent that learning-by-doing is a form of human capital, foregone output measures the total human capital investment. That is, in standard treatments such as Becker [1965] or Hashimoto [1981], investment in firm specific human capital is shared between the firm and the worker and the total investment is measured as the foregone output (the worker's share being any foregone wages). Some human capital aspects of learning-by-doing are explored below.

In either case, Table 8 provides some picture of the size and distribution of this investment. The calculated investments in learning are roughly half the size of the investment in physical capital for each plant. Mean learning investment overall was about a million dollars, averaging to about $15,000 per employee. The magnitude of the investment in the largest plants—the group that plays such a dominant role in aggregate adjustment behavior—is particularly striking. For this group the investment represents nearly a third of one year's output and an average investment of nearly $37,000 per employee. By comparison, average production worker annual earnings for this group was $19,200 in 1987 dollars; non-production workers averaged $32,700 per year. Thus the investment in learning-by-doing was quite large compared to typical estimates of investment in formal job training and accounting estimates of labor adjustment costs, both of which are only a fraction of a year's wages [Bessen, 1997, Hamermesh and Pfann, 1996].

Finally, Table 8 calculates the share of total learning investment accounted for by different groups. Again, the largest plants account for a disproportionate share—65% of the total. Multi-plant firms account for 97%. Thus although all size classes show evidence of multi-factor productivity growth and hence evidence of learning-by-doing, the actual investment in learning is highly concentrated among the top 10% of plants ranked by size. This further suggests substantial plant heterogeneity and the importance of aggregation effects in overall industry statistics.

Learning-by-doing and wages

The above analysis of adjustment patterns concluded that plants, especially large plants, increase productivity by improving labor quality. This quality improvement could result from new skills or knowledge acquired by workers (a human capital interpretation) or it could result from changes in the composition of the labor force (a selection or job-matching interpretation). But in either case, the quality improvement occurs for a specific worker-plant match. It is the specificity of this match—in contrast to the model of Hicks neutral technical change—that gives rise to the observed rising labor productivity and non-decreasing capital intensity.

This suggests a particular interpretation of learning-by-doing. In contrast to some explanations that treat the productivity improvement as a non-specific "organizational learning," the model here is one of "labor learning-by-doing" (although in the job-matching interpretation the actual knowledge gained may be possessed by managers).

If this interpretation is correct, then some corroboration might be found in wage data. That is, to the extent that learning-by-doing represents an investment in specific worker-plant matches, then one might expect to find a relationship between plants with higher learning and plants with higher wages. Standard models of firm-specific human capital [Becker, 1965, Hashimoto, 1981] suggest that workers have an opportunity for *ex post* bargaining and so firms will pay higher wages in later periods. Selection models suggest that firms selecting better quality workers will also pay them higher wages. Jarmin [1996], using a production function analysis, has found such a relationship for the instrument industry.

Also one might expect to find a relationship between learning and the *change* in wages over the course of the ramp-up. The standard result for firm-specific human capital is the upward sloping wage-tenure profile. Similarly, in a selection model one would expect the higher productivity workers remaining after selection to be paid higher wages. Neither relationship, however, should exist if the productivity change results from non-specific organizational learning.

Columns 1-4 of Table 9 show regressions of log hourly wages and log annual salaries against a variety of plant characteristics including the five year growth in multi-factor productivity as a measure of learning-by-doing. The second in each pair of regressions includes a term for the plant's productivity relative to industry productivity. Both production wages and non-production salaries are positively and significantly associated with productivity growth. Although the coefficients are not large—they are likely to be highly attenuated due to missing variables—they are statistically significant, highly so for production workers.

Columns 5-8 show regressions on the change in log wages and salaries over the first five years. Again, these are both positively and significantly associated with productivity growth.

For both sets of regressions, the quantities measured are plant averages and so one cannot distinguish between higher wages for individual workers and change in the composition of the workforce to one with average higher wages. Both sorts of change, however, are consistent with the hypothesis of improving labor quality. In one case, individual worker's wages increase with individual's skills; in the other case, the average quality of the workforce improves as better job matches are selected.[15]

[15] It is possible that the composition of the workforce could improve without any sort of learning process—that is, firms might choose to replace lower quality workers with higher quality workers even though the firm could have hired the higher quality workers in the first place. Since such behavior seems implausible and costly in a world with adjustment costs, improvement in labor quality over the first five years is inferred to result from a learning process.

Note that these results suggest that learning-by-doing is associated with labor specific quality improvement for *both* production and non-production workers. This contrasts with the analysis of Bartel and Lichtenberg [1987] who proposed that learning-by-doing is dominated by non-production workers hence the proportion of non-production workers should decline with the age of the plant.[16] Moreover, the data shown here (Table 1) shows the proportion of non-production workers *increasing* over the first five years of the plant.

Note also the effect of plant size on wage level. Other researchers have found a strong positive correlation between these two variables [Troske, 1994] and this is also apparent in the coefficients of size class dummy variables. However, the range of variation in these coefficients is not all that large, suggesting that a portion of the wage premia paid at larger plants may be related to the greater role of learning-by-doing at these plants.

In sum, the association of higher wages and greater wage increases with productivity growth corroborates the important role of learning-by-doing in adjustment behavior.

Learning-by-doing after plant startup

The analysis so far has been entirely concerned with the behavior of new plants. Although one would expect plants to behave after startup much as they behaved during startup, this is not necessarily so. It is important to question whether post-startup behavior is similar, even though the evidence one way or the other may not be very complete.

In particular, because the learning-by-doing model seems to provide the dominant explanation for startup behavior, one wonders whether adjustments to subsequent shocks demonstrate a similar pattern of behavior. This is a particularly interesting question because almost all of the empirical literature on learning-by-doing has studied new plants only.

To this end, a separate analysis was performed on a sample of plants that were continuously reported in the LRD with the aim of identifying episodes where employment shocks occurred. Two sub-samples were extracted, one where plants experienced large increases in production employment (Positive Spikes) and one where plants experienced large decreases (Negative Spikes). [17]

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[16] Bartel and Lichtenberg examined a longer time period; however, since most of the productivity gain associated with learning-by-doing occurs during the first couple years, it would seem that the relevant changes in labor composition would occur during these first years.

[17] Thanks to John Haltiwanger for providing the file of plants reported in every Census of Manufacturing and Annual Survey of Manufactures from 1972 - 93. After screens for reporting error, this base file consisted of 10,916 plants. The “Positive Spike” extract consisted of plants experiencing an increase in production employment of 20% or more and no change in change in production employment

Table 10 reports summary statistics and productivity changes for these two extracts. Note first that the continuity requirement strongly affects the nature of the sample, which is composed predominately of large plants and plants owned by multi-plant firms. Nevertheless, these samples can be compared to the group of large startup plants.

Both extracts show a statistically significant multi-factor productivity increase. Both the productivity change and the learning investment per employee are quite similar to the measures obtained for the group of large startup plants, especially for the Negative Spike sub-sample. For this group the learning investment averaged \$31,000 per employee compared to \$37,000 per employee found for the large startup plants above. Thus it would appear that a similar sort of learning-by-doing does occur among continuing plants.

Note that the learning measures for the two sub-samples are quite different, suggesting a very asymmetric labor adjustment. The implicit cost of a large downward adjustment is much larger than the cost of an upward adjustment. This supports the asymmetric pattern found by Baily, Bartelsman and Haltiwanger [1996]. It is possible that upward adjustments can be accommodated by adding new workers and a learning investment need only be made in these workers. On the other hand, downward adjustments may frequently entail a re-organization of the entire work process (downward adjustments tend to happen in plants that are in long-term decline) thus requiring that investments be made for all or most workers.

In any case, these results suggest that learning-by-doing does play a significant role in plant behavior on an ongoing basis after startup.

V. Conclusion

The empirical literature on learning-by-doing has been largely separate from research dealing with plant dynamics and growth. Most of this learning literature consists of case studies that are difficult to relate to more general research (some notable exceptions include Bahk and Gort [1993] and Jarmin [1996]).

The picture of new plants developed here suggests that this is unfortunate. Learning-by-doing seems to play an important role in startup dynamics, in adjustments to shocks and in wage determination. Large plants in particular appear to make substantial investments in this intangible

greater than 20% up or down for the next 4 years. The "Negative Spike" extract consisted of plants experiencing a 20% decrease in production employment and no large change for the subsequent 4 years.

quantity. Although this investment may be difficult to observe and measure, it may be important to understanding a variety of micro and macro phenomena.

More generally, the rich and varied picture of adjustment behavior among new plants re-emphasizes the importance of developing aggregate models based on micro-models and micro-data.

Appendix – Sample and Data Construction

The sample of new plants is extracted from the LRD from all industries except tobacco. It is a balanced panel of plants that survived at least five years and for which we have annual data for each of the initial five years. The sample includes only plants which were reported as new their first reported year, beginning in years 1972 - 87. Plants with missing or imputed data were excluded as well as plants that had capital changes greater than **ln** 2 between years three and five (such plants were either re-starting or dismantling) and plants where the change in the ratio of output to deflated materials changed by more than **ln** 2 between years one and two and between years four and five (probable reporting error).[18]

This resulted in a sample of 5,625 plants. Characteristics of these plants are shown in Table 1. The selection criteria used to derive this sample tend to slightly under-represent small plants and plants owned by single-plant firms. To weight these characteristics a second sample was extracted from the Census of Manufacturers of all plants that first entered during years 1972, 1977, 1982 or 1987, and that also survived at least until the following Census.[19] To make the analysis more representative of new entrants generally, weights were derived from this Census panel based on size class and single-plant ownership status and these weights were applied to the 5-year startup panel for all subsequent analysis. This weighting procedure did not affect results substantively.

Output is measured as the sum of shipments plus the change in inventories deflated by the appropriate 4-digit SIC deflator from the NBER Productivity database developed by Wayne Gray and Eric Bartelsman [1996]. The input factors used in productivity calculations are production hours, non-production workers, the deflated sum of materials, purchased services and energy, and capital.

[18] Additional screens were provided to check for large changes in rentals of plant and equipment where annual rentals are greater than capital stocks and also for decreases in inventories that exceeded 2/3 of shipments (indicating a possible change in inventory accounting method).

[19] This sample excludes plants with zero shipments or production workers or imputed values.

Net real capital was constructed using a perpetual inventory method where initial gross capital and investments in plant and equipment were deflated by 4-digit deflators developed by Bartelsman and Gray. Since capital is new, any depreciation series based on stochastic retirements is inappropriate. Additionally, we found relatively high levels of capital retirements during the initial years, tapering off to more normal levels by the fifth year—44% of the plants experienced retirements greater than 10% of their final capital stock! Although retirements are usually seen as the result of declining useful service efficiency, a high level of retirements is, in fact, consistent with learning-by-doing—initial capital purchases, made when managers have the least knowledge of operations, are frequently inappropriate or inefficient and thus often retired early. Accordingly, capital stocks were assumed to decay according to a beta function representing the efficiency of their services and retirements were accounted for explicitly.[20] For productivity calculations, capital stocks also included deflated inventories and rental expenditures for equipment and structures divided by an industry rental rate (see below).

Output shares for production and non-production labor were calculated as 1.17 times the respective wage bill over current-dollar output to account for mandatory employer payroll taxes and benefits.[21] The output share for materials, purchased services and energy was simply the ratio of expenditures on these items to current-dollar output. Capital output shares were calculated by applying a capital rental rate to the current stocks. Rental rates were calculated using the 2-digit BLS series for current dollar capital cost divided by the total capital stocks for the corresponding industry from the NBER Productivity database. Note that this approach does not impose an assumption of constant returns to scale.

The productivity calculations for the Positive and Negative Spike files were similar except that capital was constructed differently, as here stochastic retirements incorporated in the depreciation measure are appropriate. Capital was calculated on a perpetual inventory basis using 2-digit BEA deflators and 2-digit BEA depreciation series. The details used are the same as those

[20] We used the BLS beta function where capital services at time t are $K(t) = K_0 \cdot (L-t)/(L-b \cdot t)$ where K_0 is the initial value of the capital and L is the useful service life, and β = 0.5 for equipment and 0.75 for structures. Industry service lives were taken from the BEA series of service lives by asset type and the asset type mix for each industry was derived from the 1977 Input-Output tables. Note that the LRD only reports retirement data for 1977 - 87. Prior to 1977 retirements were imputed as $\min(0, I - \Delta G)$ where I is investment and ΔG is the change in gross book value capital.

[21] The figure 1.17 was calculated as the mean ratio of employment compensation to wages and salaries in the NIPA series for manufacturing workers 1972 - 87.

described in Adams and Jaffe [1994]. Rentals were not included and retirements were not included explicitly, but are included as a stochastic term in the BEA depreciation figures. Other aspects of the productivity calculation remained the same.

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Figure 1. Mean Values of Variables as a Percent of Fifth-Year Levels
Note: Means for sample of 5,625 plants.

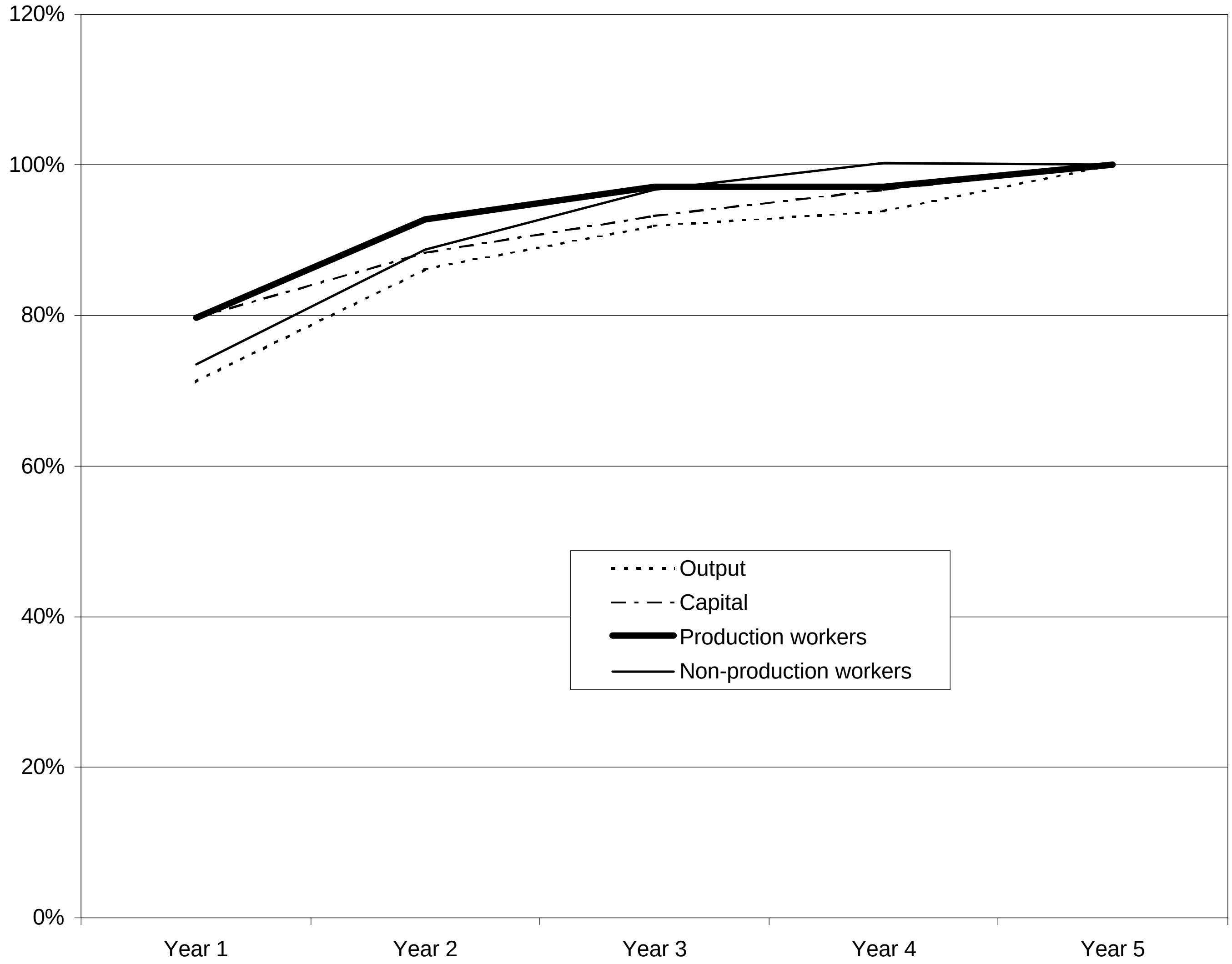

Table 1. Overall Characteristics of Adjustments at New Plants

	Year 1	Year 2	Year 3	Year 4	Year 5	5 Year Growth Aggregate	Mean
Output	$ 5,428	$ 6,570	$ 7,004	$ 7,152	$ 7,622	34%	32%
Materials	$ 3,104	$ 3,862	$ 4,018	$ 4,153	$ 4,387	35%	33%
Capital	$ 2,904	$ 3,221	$ 3,398	$ 3,526	$ 3,646	23%	28%
Capital + rental capital	$ 3,207	$ 3,607	$ 3,854	$ 3,985	$ 4,106	25%	24%
Inventories	$ 801	$ 982	$ 1,078	$ 1,096	$ 1,159	37%	26%
Total Employees	57.2	67.4	71.2	71.8	73.4	25%	29%
Production workers	43.8	51.0	53.4	53.4	55.0	23%	27%
Production hours	83.9	98.7	103.3	102.4	106.9	24%	28%
Production worker hourly wages	$9.11	$9.07	$8.89	$8.87	$8.91	-2%	-2%
Non-production workers	13.6	16.4	17.9	18.6	18.5	31%	34%
Non-production salaries	--	$32.1	$31.8	$32.3	$32.1	0%	-8%

Notes: Means for entire sample of 5,625 new plants. All analysis used sample weights as described in the Appendix. Dollar amounts are in thousands of 1987 dollars, except hourly wages, which are in 1987 dollars per hour, and production hours are in thousands. Deflators are from Bartelsman and Gray [] except for wages and salaries, which are deflated using the CPI. Materials include energy costs and purchased services. Rental capital is imputed by dividing rental equipment and structures by the BLS capital rental rates. Non-production workers is the number on March 12 of the year and non-production salaries are computed by subtracting production wages from the plant's total wage and salary bill and then dividing by the number of non-production workers. Since this procedure is inaccurate for years with rapid growth in the number of non-production workers, this quantity is omitted for the first year. Aggregate growth rate is the log growth of the sum over all plants for each given quantity; mean growth is the mean of the log growth calculated for each plant.

Table 2. Estimates of the Time Structure of Adjustment

	Unrestricted GMM First-differenced equations		**Restricted Model (*l* = 0) GMM First-differenced equations**				**Restricted Model (*l* = 0) OLS Levels with fixed effects**			
	Capital	Capital + Rentals	Capital	Prod. Workers	Prod. Hours	Non-prod. Workers	Capital	Prod. Workers	Prod. Hours	Non-prod. Workers
l	.739 (.212)	.751 (.287)	--	--	--	--	--	--	--	--
λ	.677 (.091)	.747 (.092)	.984 (.053)	.929 (.025)	.928 (.026)	.971 (.069)	.491 (.005)	.636 (.007)	.671 (.009)	.521 (.006)
Test of Restriction χ^2 [d.f.]			11.64 [1] P = .001	1.35 [1] P = .246	1.15 [1] P = .284	5.83 [1] P = .016				
Mean lag excluding pre-production delays (years)	.12	.08	.02	.08	.08	.03	1.04	.57	.49	.92
Over-identifying restrictions χ^2 [d.f.]	2.41 [2] P = .300	1.95 [2] P = .377	5.80 [3] P = .122	1.33 [3] P = .722	2.47 [3] P = .480	5.94 [3] P = .114				
Adjusted R^2							.477	.350	.253	.383
Number of cases	5,625 with 4 eqns.		5,625 with 4 eqns.				22,500 pooled (excludes 1st year)			

Notes: Standard errors are in parentheses; standard errors are asymptotically heteroscedastic-consistent. The GMM regressions were performed on the first-differenced set of equations described in (3) using the right hand side variables as instruments. Setting $l = 0$ reduces this model to the simple partial adjustment model. This restriction was tested and rejected for capital. However, the unrestricted regression did not converge for some variables and so a slightly different nesting model was used: the first equation in (3) was replaced with $\Delta K_1 = (1-\lambda_1)\cdot K_0$. This unrestricted model was estimated and then a version was tested with the restriction $\lambda_1 = \lambda$ imposed. The restricted regression used the weighting matrix from the unrestricted regression. A test of this restriction was performed by comparing the criterion function (the sum of squares of the moment conditions) for each model. As shown, the restriction was only rejected for capital and so results for the unrestricted model are only shown for capital. The over-identifying restrictions or Sargan test is a test of the fit of the moment conditions based on the criterion function. First-differencing in panel data aggravates measurement error problems [Griliches and Hausman, 1986]. For this reason the restricted model was also estimated in levels with fixed effects for each plant. The unrestricted model cannot be estimated this way.

Table 3. Characteristic Patterns of the Labor Adjustment

	Aggregate	Mean	Models: Convex Adjustment Costs	Time-to-build	Neutral Technical Change	Learning-by-doing
Change in capital intensity			< 0	< 0	< 0	≥ 0
Change in log capital per employee	-.022	-.011 (.015)				
Change in log capital per production worker	.000	.014 (.016)				
Change in labor productivity			< 0	0	0	> 0
Change in log output per employee	.091	.024 (.016)				
Change in log output per production worker	.112	.049* (.016)				
Change in multi-factor productivity			0	$\alpha \cdot \Delta \ln \frac{K}{L} > 0$	> 0	> 0
Change in log M		.057* (.006)				
$\Delta \ln M - \alpha \cdot \Delta \ln \frac{K}{L}$		.032* (.007)				

Notes: The aggregate changes reported are the changes in quantities summed over all 5,625 plants. The means are mean values for each plant. Standard errors of the means are provided in parentheses and changes that are significant at the 1% level have asterisks. Capital and output are real values in 1987 dollars. Multi-factor productivity is calculated as a Divisia index between years 1 and 5 using production hours, non-production employment, materials cost (including the costs of materials, parts, fuels, electrical energy, purchased communications and contract work), and real capital (including equipment, plant, inventories and the services of rented plant and equipment). The adjusted productivity calculated in the last row estimates α using the output share of capital for each plant and using the log of capital per production worker.

Table 4. Stability of Size and Single/Multi-plant Status

Classification Year 1	**Percent of Plants by Class in Year 5**					
	Size Class Year 5 Number of Employees				Number of Plants in Firm – Year 5	
	1-10	11-50	51-200	201+	1	2+
Size Class						
1-10	48%	48%	4%	1%		
11-50	5%	72%	22%	1%		
51-200	0%	16%	76%	9%		
201+	0%	3%	27%	70%		
No. Plants in Firm						
1					92%	8%
2+					2%	98%

Table 5. Characteristics of Plants by Initial Size and Single/Multi-plant Status

	All plants	Size Class - Number of employees year 1				Number of plants in firm	
		1-10	11-50	51-200	201+	1	2+
Number of plants	5,625	1,287	2,322	1,692	324	2,213	3,412
First year values							
Output	5,428.0	740.4	2,793.2	8,142.7	36,380.9	2,721.0	8,037.8
Capital	2,904.5	496.8	1,341.3	3,864.1	23,402.9	1,041.9	4,700.1
Employees	57.2	5.5	26.0	92.8	386.0	38.3	75.5
Production workers	43.8	4.3	20.3	74.0	272.7	31.2	55.9
Non-production workers	13.4	1.2	5.7	18.8	113.3	7.1	19.5
Mean growth rates							
Output	.316	.694	.280	.116	.081	.285	.347
Capital	.281	.552	.266	.120	.112	.384	.182
Employees	.292	.784	.252	.044	-.162	.317	.268
Production workers	.267	.744	.243	.002	-.170	.284	.251
Non-production workers	.335	.511	.325	.276	-.046	.352	.318

Notes: Output and capital are in thousands of 1987 dollars.

Table 6. Time Structure of Adjustment by Plant Characteristics

	All plants	Size Class - Number of employees year 1				Number of plants in firm	
		1-10	11-50	51-200	201+	1	2+
Unrestricted GMM Estimates of First Differences							
Capital							
l	.739	--	--	.858	.739	--	.740
λ	.677	--	--	.772	.642	--	.669
Mean Lag (excluding pre-production delays)	0.12			0.04	0.15		0.13
Test of restriction χ^2 [d.f.]	11.6 [1] P = .001	1.4 [1] P=.239	2.1 [1] P=.147	10.2 [1] P=.001	10.9 [1] P=.001	0.6 [1] P=.432	11.6 [1] P=.001
Restricted OLS Estimates of Levels (excluding first year)							
Capital							
λ	.491	.557	.591	.403	.492	.496	.490
Mean Lag (excluding pre-production delays)	1.04	0.80	0.69	1.48	1.03	1.02	1.04
Production Workers							
λ	.636	.834	.533	.652	.638	.823	.607
Mean Lag (excluding pre-production delays)	0.57	0.20	0.88	0.53	0.57	0.22	0.65
Production Hours							
λ	.671	.804	.575	.619	.709	.823	.647
Mean Lag (excluding pre-production delays)	0.49	0.24	0.74	0.62	0.41	0.22	0.55
Non-production Workers							
λ	.521	.903	.750	.735	.468	.686	.504
Mean Lag (excluding pre-production delays)	0.92	0.11	0.33	0.36	1.14	0.46	0.98

Notes: Definitions and estimations as in Table 2 and text. The unrestricted model is only shown for sub-groups where the test of smooth adjustment (expressed as a model restriction) was rejected.

Table 7. Labor Adjustment by Plant Characteristics

	All plants	Size Class - Number of employees year 1				Number of plants in firm	
		1-10	11-50	51-200	201+	1	2+
Number of plants	5,625	1,287	2,322	1,692	324	2,213	3,412
Change in capital intensity							
Change in log capital per employee	-.011	-.232*	.014	.076*	.274*	.066*	-.086*
	(.015)	(.042)	(.020)	(.022)	(.058)	(.023)	(.021)
Change in log capital per production worker	.014	-.192*	.023	.118*	.282*	.100*	-.069*
	(.016)	(.042)	(.021)	(.023)	(.060)	(.023)	(.021)
Change in labor productivity							
Change in log output per employee	.024	-.090	.028	.072*	.243*	-.033	.079*
	(.016)	(.042)	(.021)	(.022)	(.063)	(.022)	(.023)
Change in log output per production worker	.049*	-.050	.037	.114*	.251*	.001	.096*
	(.016)	(.042)	(.022)	(.023)	(.065)	(.022)	(.024)
Change in multi-factor productivity							
Change in log M	.057*	.130*	.040*	.022	.077*	.038*	.075*
	(.006)	(.014)	(.008)	(.010)	(.025)	(.008)	(.008)
$\Delta \ln M - \alpha \cdot \Delta \ln \frac{K}{L}$	.032*	.049*	.025*	.021	.095*	.039*	.026*
	(.007)	(.021)	(.009)	(.010)	(.026)	(.008)	(.011)

Notes: Means of plants for each grouping. Standard errors of means are in parentheses and asterisks designate significance at the 1% level. Calculations are as described in previous tables.

Table 8. Investment in Learning-by-doing

	All Plants	By Employees Year 1				By plants in firm	
		1-10	11-50	51-200	201+	1	2+
Mean Values per Plant							
Learning investment (1,000 1987 $)	1,087.8	132.3	357.3	667.7	14,868.7	71.7	1,967.1
Capital (1,000 1987 $)	3,645.6	830.3	1,771.0	4,569.4	29,246.2	1,413.6	5,797.3
Output (1,000 1987 $)	7,622.2	2,003.6	4,367.2	10,170.3	49,871.9	3603.4	11,496.5
Employees	73.4	17.6	41.5	113.0	403.2	49.3	96.7
Ratios							
Learning investment / output	14%	7%	8%	7%	30%	2%	17%
Learning investment / employee (1,000 1987 $ per)	14.8	7.5	8.6	5.9	36.9	1.5	20.3
Group shares							
Learning investment	100%	3%	15%	17%	65%	3%	97%
Output	100%	5%	25%	43%	26%	33%	67%
Employees	100%	6%	26%	38%	31%	23%	77%

Notes: Values are sample-weighted means of entire 5,625 plants. Output, capital and employees are values for the fifth year. Ratios are of aggregate quantities. Calculation of learning investment is described in text.

Table 9. Wages and Learning-by-doing

Dependent Variable	Log Wage/Salary Level				Change in Log Wage/Salary			
	Production worker Hourly Wage		Non-production Worker Salary		Production worker Hourly Wage		Non-production Worker Salary	
	1	2	3	4	5	6	7	8
Change in multi-factor productivity from year 1 to 5, $\Delta \ln M$	.11* (.01)	.17* (.01)	.18* (.02)	.27* (.03)	.28* (.02)	.25* (.02)	.22* (.03)	.21* (.03)
Production workers / total employment (year 1)	-.12* (.03)	-.13* (.03)	.04 (.05)	.01 (.05)	.11* (.03)	.11* (.03)	-.30* (.06)	-.30* (.06)
Size class								
1-10 employees year 1	2.25* (.05)	2.27* (.05)	3.10* (.08)	3.12* (.08)	-.12 (.05)	-.13 (.05)	.38* (.09)	.38* (.09)
11-50 employees year 1	2.30* (.04)	2.32* (.04)	3.32* (.08)	3.34* (.08)	-.06 (.05)	-.07 (.05)	.29* (.09)	.28* (.09)
51-200 employees year 1	2.33* (.04)	2.34* (.04)	3.36* (.08)	3.38* (.08)	-.05 (.05)	-.05 (.05)	.32* (.09)	.31* (.09)
201+ employees year 1	2.38* (.05)	2.39* (.05)	3.40* (.09)	3.42* (.09)	-.06 (.06)	-.07 (.06)	.38* (.10)	.38* (.10)
Capital / production worker (1987 $)	.01* (.00)	.01* (.00)	.01 (.01)	.01 (.01)	-.01 (.00)	-.01 (.00)	-.01 (.01)	-.01 (.01)
Single plant firm (year 1)	-.09* (.01)	-.09* (.01)	-.05 (.02)	-.04 (.02)	-.02 (.01)	-.02 (.01)	.01 (.02)	.01 (.02)
Multi-factor productivity relative to industry	--	.18* (.02)	--	.29* (.03)	--	-.10* (.02)	--	-.02 (.04)
Adjusted R^2	.208	.222	.066	.082	.057	.061	.021	.021

Notes: Results are for OLS regression over sample of 5,625 plants. 8 region and 63 industry dummies were included in all regressions. Standard errors are in parentheses and asterisks designate significance at the 1% level. Wages and salaries are for the 5th year of operation and are deflated by the CPI. Non-production salaries are calculated by subtracting production wages from total wages and salaries and then dividing by the number of non-production employees as of March 12. The changes in log wages and salaries are computed between the first and fifth years for production workers and between the second and fifth years for non-production workers. The change in log multi-factor productivity is a Divisia index as described above. The final variable is a measure of plant productivity relative to the plant's 4-digit SIC industry,

$$R_i \equiv \ln Q_i - \ln Q_I - \sum_{j=1}^{4} \left(\frac{s_i^j + s_I^j}{2} \right) \cdot \left(\ln X_i^j - \ln X_I^j \right)$$

where i designates the plant, I designates the industry, and X represents the input factors, production labor, non-production labor, materials and capital. Relative productivity is calculated for year 1.

Table 10. Adjustments at Continuing Plants

	Positive Spikes	Negative Spikes
Number of plants	5,600	3,853
Output, year of spike (1,000 1987 $)	90,114	72,579
Capital, year of spike (1,000 1987 $)	30,062	39,332
Employees, year of spike	623.1	571.8
Mean productivity change (year after spike to 5 years after spike)	.030 (.005)	.117 (.006)
Mean learning investment (1,000 1987 $)	8,917	17,969
Aggregate learning investment / employee (1,000 1987 $)	14.3	31.4

Note: Positive and negative spikes sub-samples were selected from a dataset of continuously reported plants in the LRD. Positive spikes were plants where production worker employment increased by more than 20% in a year and that the absolute magnitude of subsequent changes for the next 4 years was less than 20%. Negative spikes were plants where production employment decreased 20% or more and did not experience a subsequent change of absolute magnitude greater than 20% for 4 years. Quantities are as in previous tables. Note that productivity change measures exclude the year of the spike.